



Fast color contrast enhancement method for color night vision

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ABSTRACT

The increasing availability and deployment of imaging sensors operating in multiple spectral bands has led to a large research effort in color image fusion, resulting in a plethora of pixel-level image fusion algorithms. In this study a simple and fast fusion approach for color night vision is presented. The contrast of infrared and visible images is adjusted by local histogram equalization. Then the two enhanced images are fused into the three components of a *Lab* image in terms of a simple linear fusion strategy. To obtain false color images possessing a natural day-time color appearance, this paper adopts an approach which transfers color from the reference to the fused images in a simplified *Lab* space. To enhance the contrast between the target and the background, a stretch factor is introduced into the transferring equation in the *b* channel. Experimental results based on three different data sets show that the hot targets are popped out with intense colors while the background details present natural color appearance. Target detection experiments also show that the presented method has a better performance than the former methods, owing to the target recognition area, detection rate, color distance and running time.

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1. Introduction

Today, imaging sensors of various types are widely used in military and civilian applications, such as battlefield surveillance, health-care applications, and traffic control. However, the information provided by different imaging sensors may be complementary and redundant. For instance, visible images provide spectral and spatial details, and if a target has the same color and spatial characteristics as its background, it cannot be distinguished from it. While infrared image can show the existence of some special targets, such as concealed guns or people. To obtain an image that simultaneously contains the outline of scene as well as special objects for the convenience of human visual perception or for further image-processing tasks, image fusion can be used to integrate the information provided by individual sensors [1–3]. In this paper, we concern with the fusion of infrared–visible images.

During the past two decades, many image fusion methods are developed [1,3–14]. According to the color of the fused results, image fusion algorithms can be categorized into gray fusion (such as principal component analysis, contrast modulation, pyramid modulation, wavelet transform) [5–8], and color fusion. In principle, color imagery has several benefits over monochrome imagery for surveillance, reconnaissance, and security applications. The color level which human can distinguish is about hundreds times than gray level and many experiments show that color fusion may improve feature contrast, which allows for better scene segmentation

and object detection [9,13,14]. So color fusion is becoming a more and more important research field and a number of color fusion methods have been proposed [15–20].

One key topic of the color fusion is color constancy. It has been shown that the lack of color constancy with inappropriate color mapping may hinder human performance. In 2003, Toet [19,20] originally introduced color transfer technology that was ever used in color alteration among visible images [21] into multi-band color night vision, which includes visible, near infrared, and mid-wave infrared. By matching the first order statistical properties (mean and standard deviation) of the false color fused image to those of a selected natural day-time color imagery, this approach can be used effectively to give the night-vision imagery a natural color appearance. Satisfactory results can be obtained so long as the false color image and the selected reference image are similar to each other to some degree, which extends applications of the approach greatly. But color space transformations between *RGB* and *LMS*, *LMS* and $\alpha\beta\gamma$, logarithm and exponent operation are time consuming. And this method does not provide color constancy for dynamic imagery. When it is applied to a sequence of images (e.g. from a panning camera) the image statistics vary over time. As a result objects change their color over time, since the color of an object depends on its context [19,20]. To overcome above shortcomings, Hogervorst and Toet [13,14] presented a simple and fast method to consistently render multi-band night vision imagery in natural colors. Their method was implemented using standard color lookup table techniques to optimize the match between the false color fused image and the reference image. Once the lookup-table has been derived the color mapping can be deployed in real-time to

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different multi-band image sequences of similar scenes. But in the color transfer step, all three channels of the color space are processed with the same linear mapping without color contrast enhancement, that may result in low contrast between the target and the background. Targets that are clearly visible in the IR image may have the similar color to the background and are difficult to detect in the fused image, and sometimes target detection is poorer than with the IR image only.

Enhancing the color contrast is another key topic of color night vision, which improves human visual capabilities in discriminating features from their background and is essential to target detection tasks. However, to date, little attention has been paid to this problem while implementing color transfer. In [22], Wang et al. proposed a nonlinear transfer method based on local mean value of the IR after nonlinear fusion. This method can pop out the hot targets with intense red color while the background rendered natural color appearance. Zheng and Ma [23,24] proposed a novel local color night vision algorithm based on image segmentation, recognition and local color transfer to enhance the color mapping effect. However, these methods are even more expensive than Toet's original method [19,20], since they involve time-consuming procedures such as nonlinear diffusion, local recognition, local comparisons and image segmentation. In 2010, Yin et al. [25] presented one color contrast enhanced image fusion method. They introduced a ratio of local to global divergence of the IR image into the color transfer equations. As a result, both hot and cold targets are popped out, where hot targets appear intense red and cold targets appear cyan. The comparison of the color distance between the target region and the background shows that this method can bring an improvement in the hit rate for target detection than the global statistic method [25]. But due to the bad atmospheric weather, the night vision imagery is degraded by the high noise or low contrast, while the above works rarely consider this problem. To get better color night vision effects, we will present a new simple and fast color fusion method, which can enhance image quality and improve the target detection ability when bringing the natural colors. The system is shown in Fig. 1.

Based on the existed works, visible and IR images are preprocessed using local histogram equalization. Consequently, the two enhanced images are fused into the three components of an *Lab* image by means of a simple linear fusion strategy. Then the color transfer technology in simplified *Lab* color space is followed. But different from the global statistic method, the transferring equation in the *b* channel is amended by a stretch factor, which changes according to the distance between the current luminance value and the mean luminance value. In this way the final image has overall clear and natural color appearance when appropriate reference image is selected and the targets can be popped out with intense colors. This may help human observers to improve situational awareness and reduce detection time.

2. Linear image fusion method

Our fusion approach includes two steps: (1) pre-processing, (2) linear fusion.

2.1. Pre-processing

Visible images captured by charge coupled device (CCD) during night have dark background and low contrast due to a poorly illuminated environment. Generally most infrared (IR) images brought by thermal radiation have weak details and low contrast due to adverse weather and small temperature difference between target objects and their background. To improve the accuracy of scene

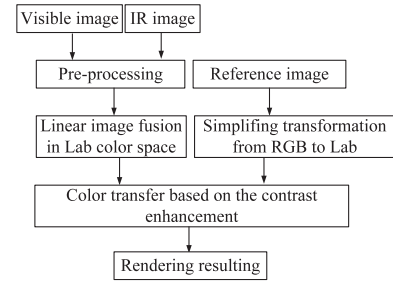


Fig. 1. A typical color image fusion system.

recognition, a pre-processing technique is needed before linear fusion.

HE is a simple and effective method for improving the quality of low contrast images that is done by stretching the dynamic range of an image's gray level. HE methods can be divided into two classes: global and local methods. Global HE method rescales pixel values in an input image (with the size of $M \times N$ and L gray levels) to cover all of the available gray level range by a cumulative distribution function (CDF) t :

$$t = \sum_{i=0}^k \frac{n_i}{n}, \quad n = M \times N, \quad k = 0, 1, \dots, L-1 \quad (1)$$

where n_i denotes the number of the pixels with gray level i .

Global HE enhances the contrast of an image by enlarging the intervals of dense gray levels and reducing those of sparse gray levels. So global HE is easy to bring over-enhancement for backgrounds and noises if they occupy many pixels and under-enhancement for targets and details with few pixels. In addition, images with extra-high contrast may easily make observer tired and anxious, which are not suitable for long time observation. To overcome these drawbacks, we introduce local histogram equalization (LHE) method into enhancing visible and IR images as followings:

Step 1: Segmenting the input image into several non-overlapping regions with the same size 5×5 .

Step 2: Operating on these regions with CDF, rather than the entire image.

Step 3: The neighboring regions are combined using bilinear interpolation to eliminate artificially induced boundaries. The new value $f'(i,j)$ at position (i,j) is:

$$f'(i,j) = (1-u)(1-v)f(i,j) + (1-u)vf(i,j+1) + u(1-v)f(i+1,j) + uvf(i+1,j+1) \quad (2)$$

where $f(i,j)$, $f(i,j+1)$, $f(i+1,j)$ and $f(i+1,j+1)$ are values before interpolation in the enhancement image, u, v are constant, $u, v \in [0, 1)$.

2.2. Linear image fusion

Different false color fusion approaches and different color spaces can be utilized in the fusion scheme. In this paper, we obtain the false color image directly in *Lab* color space. Let I_{vis} (visible image) and I_{IR} (IR image) be two input night-vision images with the same spatial resolution and dynamic range.

The false color fuse damage is brought by:

$$\begin{cases} L = m_1 \cdot I_{vis} + m_2 \cdot I_{IR} \\ a = I_{vis} \\ b = I_{IR} - I_{vis} \end{cases} \quad (3)$$

where L represents the light ness value, a and b are chrominance green–magenta and blue–yellow values separately. m_1 and m_2 are

constant coefficients ($m_1 + m_2 = 1$), which map the IR and visible images to the achromatic channel. In this way, the chromatism between the target and some spatial details can be enlarged if their colors and spatial characteristics in the IR image are similar (i.e. the plants in the fore ground in Fig. 4a). The differencing operation between the IR and visible images in the b channel provides inter-sensor contrast, making targets be popped out with possible colors. Hot targets will appear yellow and cold targets will present blue color, which agrees with our natural associations of warm (yellow) and cool (blue). To further enhance the appearance of the fused results, the L , a and b channels can be input to the following color transferring stage in which they are remapped to alternative “more natural” display.

3. Color transfer based on color contrast enhancement

The color images resulting from linear color fusion scheme often have unnatural color appearance. On the other hand, owing to the human visual system, the resolution ability to the intensity of a color image is worse than that of a gray image. Consequently, a higher hit rate for target detection can not be achieved by using only intensity information [25]. While the same operation on the three channels may make the targets have the similar color to the background. With the low color contrast, when the human performs a target detection, response time increases with indicating a serial search. So, the natural color image fusion should pop out targets in color to improve their detectability. In this section, a simple technique is described in order to pop out targets when bringing natural colors for the background. Different from [13,14,19–25], the color transfer is directly applied to a device independent Lab ($L^*a^*b^*$) color space (CIE1976). To speed up the color transfer, we first simplify the transformation between RGB and Lab color space.

3.1. Simplifying color space transformation

Lab color space is the most complete color model used conventionally to describe all the colors visible to the human eyes. Because it is a perceptually uniform color space and there is little correlation between the axes (seen in Fig. 2), different operations to different color channels can be applied with confidence that undesirable cross-channel artifacts will not occur.

The first step is to transform the RGB tristimulus values to device independent XYZ ones.

$$[XYZ]^T = M \cdot [RGB]^T$$

$$M = \begin{bmatrix} 0.4125 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \quad (4)$$

And

The forward transformations are:

$$\begin{cases} L = 116 \times f(Y/Y_n) - 16 \\ a = 500 \times [f(X/X_n) - f(Y/Y_n)] \\ b = 200 \times [f(Y/Y_n) - f(Z/Z_n)] \end{cases} \quad (5)$$

$$\text{where } f(t) = \begin{cases} t^{1/3} & t > 0.008856 \\ 7.787t + 16/116 & \text{otherwise} \end{cases}$$

Here X_n , Y_n , Z_n are the CIE XYZ tristimulus values of the reference white point. L ranges from 0 to 100 in unsigned digital format, while a and b are $[-169, +169]$ and $[-160, +160]$ separately.

To accelerate the transformation and normalize L , a and b into the range from 0 to 255, simplifications are done as follows.

Step 1: In (5), X_n , Y_n , Z_n are used to normalize X , Y , Z separately. To achieve this, we modified the standard conversion matrix M in (4) to have each line that adds up to 1 according to:

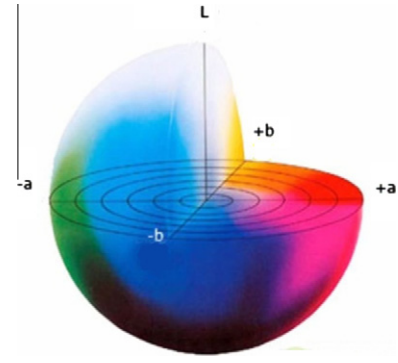


Fig. 2. Lab color space.

$$M' = \begin{bmatrix} 0.4339 & 0.3572 & 0.1899 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0177 & 0.1095 & 0.8728 \end{bmatrix} \quad (6)$$

The formula (4) is modified by:

$$[XYZ]^T = M' \cdot [RGB]^T \quad (7)$$

So the new ranges of $X - Y$ and $Y - Z$ are $[-86.784 + 86.784]$ and $[-204.9536 + 204.9536]$.

Step 2: Eq. (5) also shows that the mapping brings L the same interval as Y . a , b are the chromatism signals essentially. So conversion (5) can be amended by

$$\begin{cases} L = Y \\ a = Fa \times (X - Y) + Da \\ b = Fb \times (Y - Z) + Da \end{cases} \quad (8)$$

where Da and Db are used to eliminate the negative values, $Da = Db = 128$; Fa and Fb are coefficients of range adjustment.

Step 3: According to (6)–(8), the final transform is suggested by:

$$\begin{cases} L = Y = 0.2126 \times R + 0.7125 \times G + 0.0722 \times B \\ a = 1.4634 \times (0.2213 \times R - 0.3390 \times G + 0.1177 \times B) + 128 \\ b = 0.6196 \times (0.1949 \times R + 0.6057 \times G - 0.8006 \times B) + 128 \end{cases} \quad (9)$$

After color processing, which will be explained in the next section, we must transfer the result back to RGB via XYZ color space following the adverse transformation to the above. We convert Lab color space back to RGB using:

$$\begin{cases} R = L + (0.0120 \times a1 + 0.0021 \times b1) \\ G = L - (0.0036 \times a1 + 0.0002 \times b1) \\ B = L + (0.0002 \times a1 - 0.0045 \times b1) \end{cases} \quad (10)$$

$$\text{where } \begin{cases} a1 = 174 \times (a - 128) \\ b1 = 410 \times (b - 128) \end{cases}$$

3.2. Color transfer based on color contrast enhancement

To get natural appearance, color transfer based on statistical method is implemented to render the fused image with the colors similar to a reference day-light image in the simplified Lab space.

Firstly, the mean is subtracted from the fused image data points:

$$\tilde{L} = L - \langle L_{fue} \rangle \quad \tilde{a} = a - \langle a_{fue} \rangle \quad \tilde{b} = b - \langle b_{fue} \rangle \quad (11)$$

Then, the data points are scaled with the ratio of the standard deviation of the fused image to that of the reference image:

$$L' = \frac{\sigma_{ref}^L}{\sigma_{fue}^L} \tilde{L} \quad a' = \frac{\sigma_{ref}^a}{\sigma_{fue}^a} \tilde{a} \quad b' = \frac{\sigma_{ref}^b}{\sigma_{fue}^b} \tilde{b} \quad (12)$$

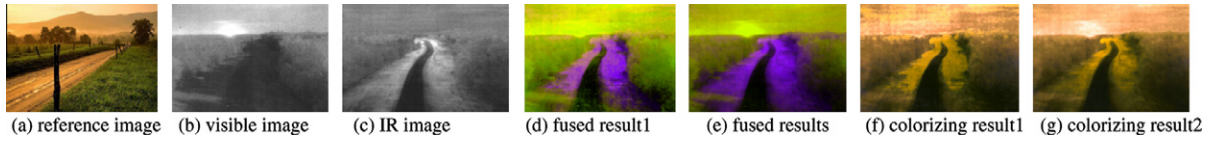


Fig. 3. Data set 1.

Finally, instead of adding the averages that we previously subtracted, we add the averages computed for the reference image.

From Eq. (12), we can see that the values of each pixel in the fused image are globally modified by the same scaling factor $\sigma_{ref}/\sigma_{fuse}$. Hence, the intensity of the hot targets in IR is weakened, which brings ambiguous targets and will reduce the recognition efficiency. To enhance the color contrast between the target and background, we process each pixel in the blue–yellow channel with a stretch factor w :

$$b' = w \cdot \frac{\sigma_{ref}^b}{\sigma_{fuse}^b} \tilde{b} \quad (13)$$

In the IR image, the hot targets have larger luminance values and the cools have smaller values. To maintain these characteristics, the stretch factor $w(i,j)$ of each pixel (i,j) in the fused image is defined as:

$$w(i,j) = k \cdot \text{dist}(i,j) / \langle \text{dist} \rangle \quad (14)$$

$$\langle \text{dist} \rangle = \frac{\sum_{i=1}^m \sum_{j=1}^n \text{dist}(i,j)}{m \times n} \quad (15)$$

$$\text{dist}(i,j) = \|L(i,j) - \langle L \rangle\| \quad (16)$$

where k is a constant that can be modified according to the actual requirement for the enhancement. $\text{dist}(i,j)$ denotes the luminance divergence of the pixel (i,j) from the mean intensity of L channel in the fused image. $L(i,j)$ and $m \times n$ are luminance value of the pixel (i,j) and the size of the fused image separately.

As both hot and cold targets are of great divergences from the mean intensity of L channel, both of them can be enhanced. With color contrast enhancement, hot targets will appear intense yellow, while cold targets will appear intense blue in the fused

image. The yellow color of the targets can alert observers of possible danger, and the blue color can help observers to detect cold targets or low temperature regions. And meanwhile the global transfer method brings the natural colors for details. Finally, we convert the result back to RGB via Eq. (10).

4. Colorizing results on image sequences

To validate the effectiveness of our method, a pair of night vision images and two image sequences are tested. For comparison, we also obtain the color fused image sequences by Toet's method without enhancement [19] and by Yin's enhancement method [25]. Subjective results show visible color contrast enhancement between the target and background in the final fused images.

Fig. 3 shows the comparison between different pre-processing methods. Fig. 3d and e is the results of the linear fusion after global HE method and LHE method respectively. Fig. 3f and g is the color rendering results of Fig. 3d and e respectively. It can be seen that using the same reference image (Fig. 3a) the linear fused method based on LHE is relatively more robust with background and targets than that based on global HE. In the transfer result after linear fusion based on global HE, targets are weakened and the contrast is not good. Linear fusion based on LHE can bring clearer and more natural scenes (Fig. 3f).

Fig. 4 is the comparing experiment among our method, Toet's (2003) and Yin's methods. To make the colorizing results generally applicable, we select 10 pairs of IR and visible images from data set “UN camp”. For the “UN camp” sequence, the man is the hot target, and the top region of the house is a cold target in the IR image. As analyzed in Section 2.2, the man and the top region of the house should appear yellow and blue respectively in the 10 color fused results. In Fig. 4c brought by Toet's global statictic method, however, without color contrast enhancement and pre-processing, the

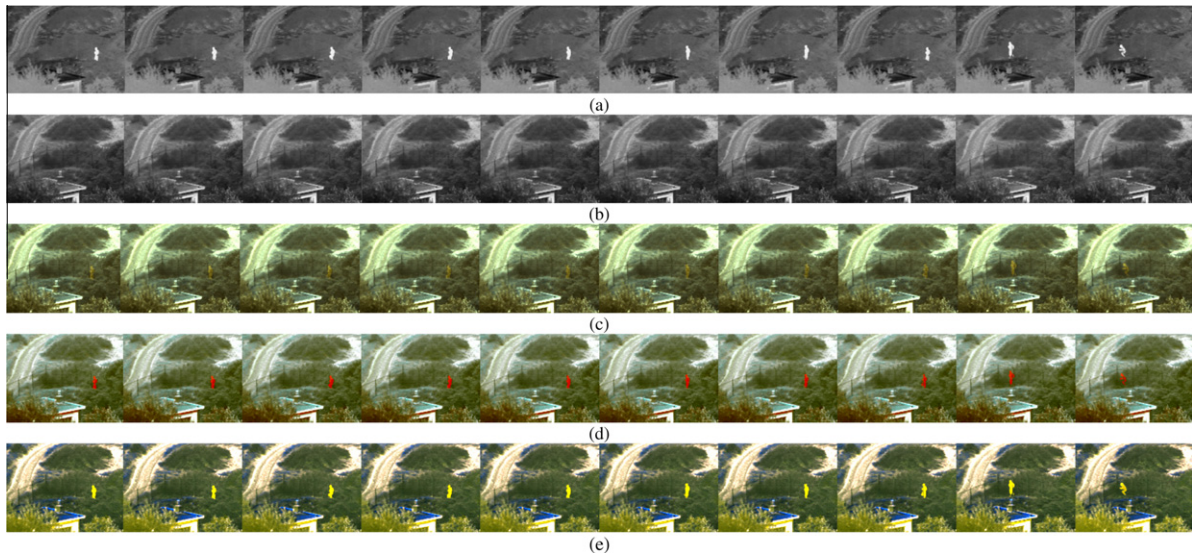


Fig. 4. IR and visible image fusion from “UN camp” sequence: (a) IR image; (b) visible image; (c) colorizing results without enhancement; (d) colorizing results by Yin's method; (e) colorizing results by our method.

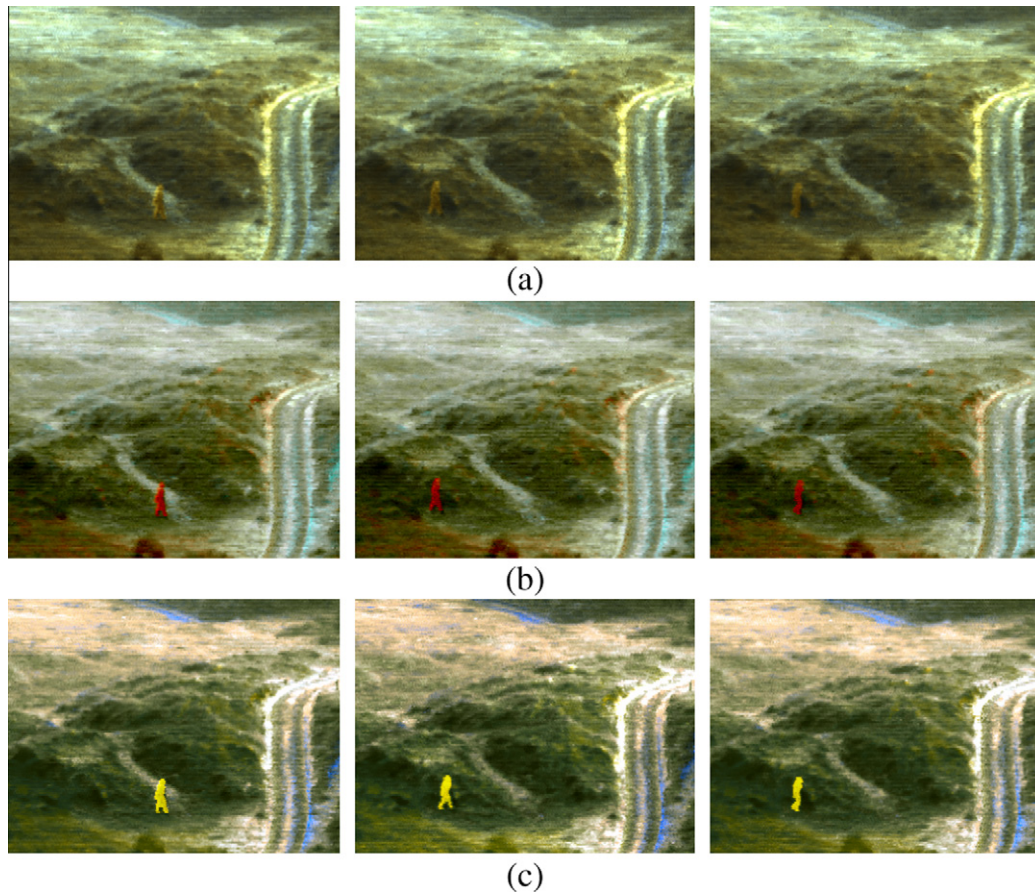


Fig. 5. Colorizing fused results of three pairs of IR and visible images from “Dune” sequence. (a) Colorizing results without enhancement; (c) colorizing results by Yin’s method; (d) colorizing results by our method.

man takes on almost the same color as the background and is very difficult to detect. Fig. 4d and e is the colorizing results brought by Yin’s method in YUV space without pre-processing and our method separately. It can be seen that Yin’s and our enhancement methods can give considerable boost to the color of the hot and cold targets. The man appears intense red in Fig. 4d and intense yellow in Fig. 4e.¹ The roof presents deep blue in the two colorized images. When comparing with Yin’s method [25], Fig. 4 shows that the details in Fig. 4e are richer and clearer than those in Fig. 4d because LHE can improve the image contrast.

The same conclusion can be deduced from the experiment using another 10 pairs of IR and visible images from data set “Dune”. Fig. 5 gives the color fused results of three pairs among the image sequence. Fig. 5a–c is the results respectively produced by Toet’s, Yin’s and our methods. As we can see in Fig. 5a, without pre-processing and channel’s enhancement the man is hard to be distinguished from the background. Yin’s method provides better results as the human appears red. Our method also brings better results as the human appears intense yellow, and thus the target can be easily distinguished from the background. The background takes on intense cyan, which will help judge the temperature distribution of the scene, though there is no cold target.

5. Discussions

Human visual inspection will be a good choice to evaluate colorized images. However, the reproduction of subjective tests is of-

ten time-consuming and difficult, while the exact same conditions for the test can not be guaranteed. Unfortunately, to the best of our knowledge, there is no effective and well-accepted objective metric for color fusion schemes. However, as we aim at improving the identification ability of the targets by pre-processing and enhancing methods, we can roughly evaluate different color fusion methods through their detectabilities of the target and their abilities of target-background separation. Before giving the evaluation metrics, we first extract targets from the background. For IR images, the targets can be gotten using the threshold segmentation, which will be looked as the ideal detection results. For color fusion images, we first produce different color fields by *K*-means clustering, then adopt threshold segmentation to extract targets. In the case of image sequence “UN camp”, man and roof are the hot and cold targets separately. In “Dune” sequence, only human is the hot target without cold target.

Then we evaluate different methods by calculating target’s recognition area, detection rate and the color distance between the background and target. The recognition area *S* can be defined as the sum of pixels in the target field. The detection rate *rate* is described as:

$$rate = \frac{num_{correct}}{num_{ideal}} \quad (17)$$

where $num_{correct}$ denotes the sum of pixels detected correctly, that is to say the corresponding pixels in the detected target to those in the ideal target. num_{ideal} is the number of pixels in the ideal target.

The parameters *S* and *rate* only evaluate the targets’ detection ability from target itself, while they cannot embody the difference between the target and the background. If the target has the same color and spatial characteristics as its background, the detection

¹ For interpretation of color in Figs. 2–7, the reader is referred to the web version of this article.

Table 1a

Comparisons of recognition for different methods using “UN camp” sequence.

Recognition area	1	2	3	4	5	6	7	8	9	10
S_{ideal}	458	462	466	455	447	450	476	511	498	400
S_{glo}	390	372	373	385	388	377	393	406	423	211
S_{Yin}	350	371	364	363	355	349	365	359	394	270
S_{our}	398	390	405	409	395	395	425	440	434	347

Table 1b

Comparisons of recognition area for different methods from “Dune” sequence.

Recognition area	1	2	3	4	5	6	7	8	9	10
S_{ideal}	316	288	350	290	349	305	347	355	314	341
S_{glo}	316	292	341	310	340	296	317	332	326	323
S_{Yin}	257	268	336	273	272	235	270	265	225	249
S_{our}	297	271	307	284	330	293	323	336	304	326

rate may be large, but it is difficult to be distinguished from the background. So we also measure the color distance between the target region and its surrounding region. The distance D is defined as the Euclidean distance in Lab color space:

$$D = \sqrt{(\langle L_t \rangle - \langle L_b \rangle)^2 + (\langle a_t \rangle - \langle a_b \rangle)^2 + (\langle b_t \rangle - \langle b_b \rangle)^2} \quad (18)$$

where t, b stand for the target and the background regions, respectively. $\langle \rangle$ is the mean value. The background is defined as the set containing all pixels in the region surrounding of the target in the color fused image.

Tables 1a and 1b show the comparisons of hot target's recognition areas with different methods. The recognition areas of ten color fused results from “UN camp” sequence are listed in Table 1a. Those of “Dune” sequence are listed in Table 1b. S_{ideal} , S_{glo} , S_{Yin} and S_{our} represent the target's recognition areas of IR image, global colorizing method, Yin's method and our method separately.

It can be seen that the recognition areas produced by our method are bigger and much closer to the ideal values when comparing with the Toet's (2003 without enhancement) and Yin's methods.

Fig. 6 gives the Bar graphs of the detection rate with different fusion methods. X-axis and Y-axis present image sequence number and detection rate value respectively. Note that the detection rate values for the hot targets in the “UN camp” and “Dune” sequences correspond primarily to the recognition area; So the detection rate brought by Yin's method is generally smaller than that of the method without enhancement, although the target is popped out with red color. The detection rate of our method is comparable, but slightly larger than that of Toet's method (2003, without enhancement). In addition, the targets with intense yellow color in our fused results are more perceptible.

Fig. 7 shows the comparison of color distances in the simplified Lab space for different methods. Yin's method enlarges the distance between the hot target and the background drastically due to the intense red color. While the distance provided by our method is more than 3–4 times than that of the general fusion scheme without enhancement. Besides, Yin's and our methods both can enlarge the color distance between the cold target and the background, indicating that the cold target is enhanced. However, as the color distance for cold target brought by our method is larger than that of Yin's method (seen in Fig. 7b), the proposed method can provide a better enhancement result. In addition, our method raises the target's recognition area and detection rate seen from Table 1 and Fig. 6.

The effectiveness of the proposed method can be further explained through the running time. Table 2 gives the average run-

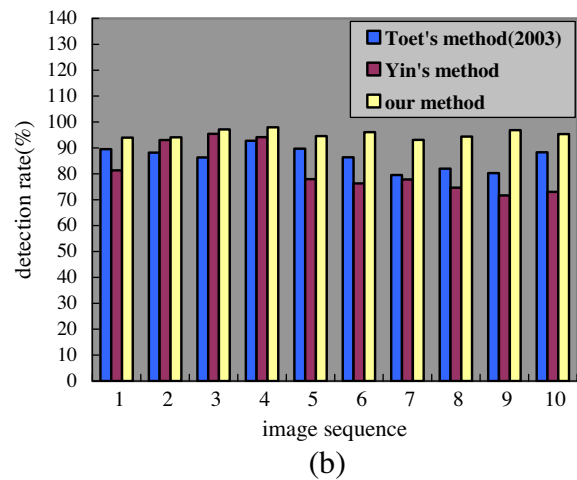
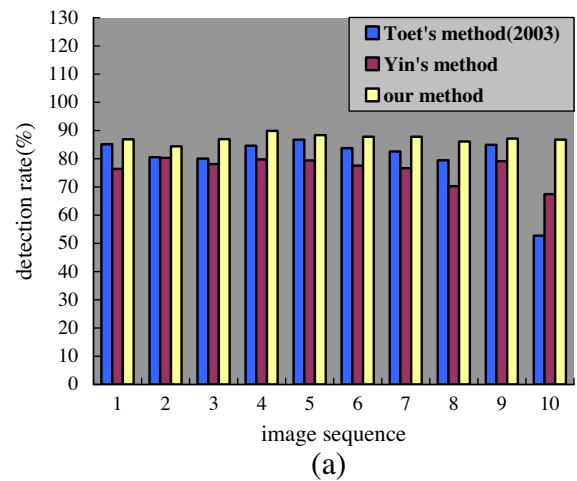


Fig. 6. Bar graphs for the detection rate with different image fusion methods: (a) Bar graph for the “UN camp” sequence; (b) Bar graph for the “Dune” sequence.

ning time of ten color fused results for different methods on a Intel (R) Core™2 Duo 1.50 GHz CPU and 0.99 GB memory using MATLAB code. It can be easily seen that the proposed method in the simplified Lab color space is the fastest. Because it only needs a linear transformation between different color spaces and avoids clustering and complex transformations between different color spaces.

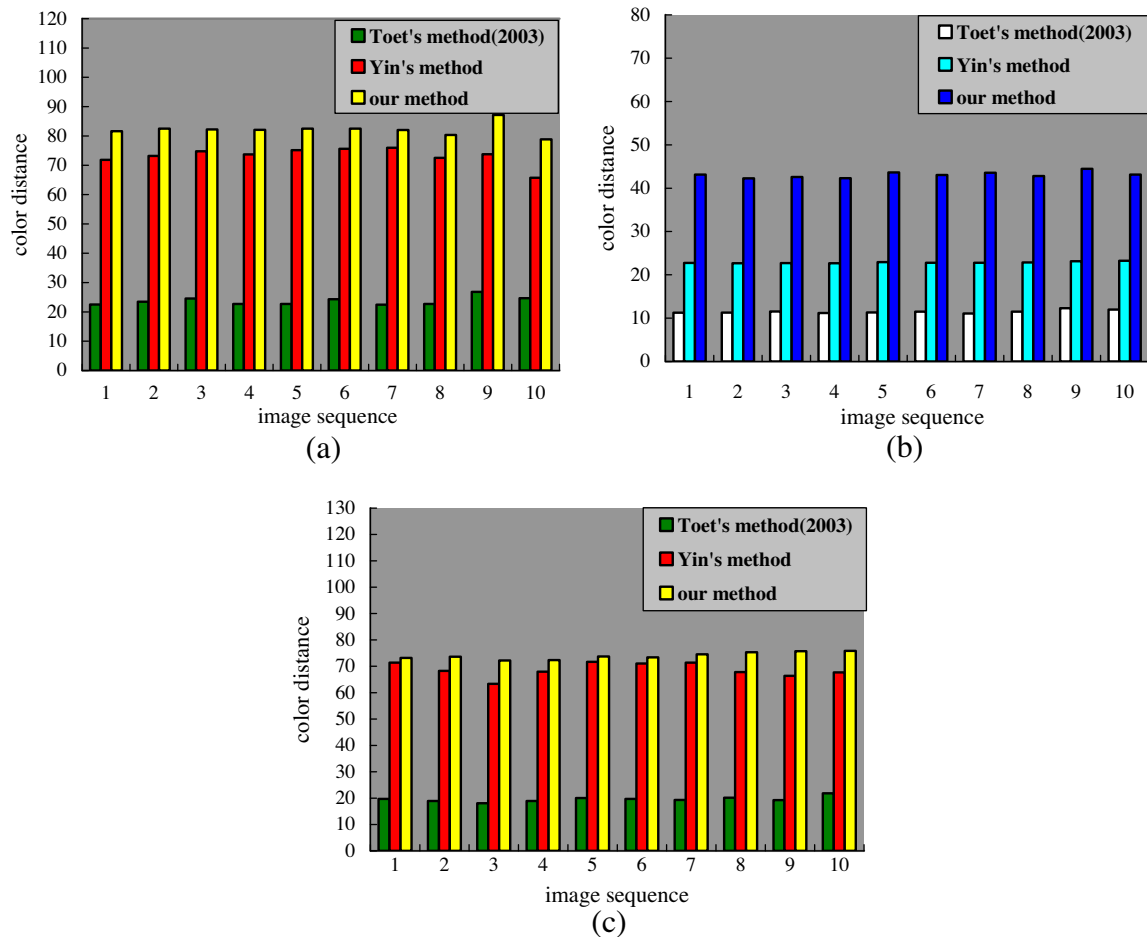


Fig. 7. Bar graphs for the color distance between the targets and the background with different image fusion methods: (a) color distance between man and his background for the "UN camp" sequence; (b) color distance between the roof and its background for the "UN camp" sequence; (c) color distance between the human and his background for the "Dune" sequence.

Table 2
Running time (s).

	Toet's method (2003)	Yin's method	Our method
"UN camp"	0.9518	0.7717	0.6960
"Dune"	0.9477	0.75177	0.7044

6. Conclusions

In this paper, we discuss a simple and effective fusion method of visible and IR images for night color vision. Before fusion, local histogram equalization is introduced to improve the visible and IR images' quality. Then a simple linear fusion method is proposed. In order to get the natural colors and improve the target detection ability, an amended global color transfer method is applied. Under the control of the stretch factor, the targets can be popped out and meanwhile the backgrounds are rendered with natural colors. From the experiments results, our algorithm is competitive with the former methods

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